

Cloud Computing: Web-Scale Information Processing with MapReduce



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“Web-Scale” Problems

- Emergence of data-intensive problems:
 - Problems involving the Web (e.g., crawling, searching)
 - “Post-genomics era” in life sciences
 - Data from accelerator experiments, remote sensors, ...
 - Web 2.0 applications
 - High-quality animation
- How can we practically tackle these problems?



How much data?

- CERN's LHC will generate 15 PB a year (2008)
- NOAA has ~1 PB climate data (2007)
- Wayback machine has ~2 PB (2006)
- Google processes 20 PB a day (2008)
- "all words ever spoken by human beings" ~ 5 EB



640K ought to be enough for anybody.

Relevance to HCI

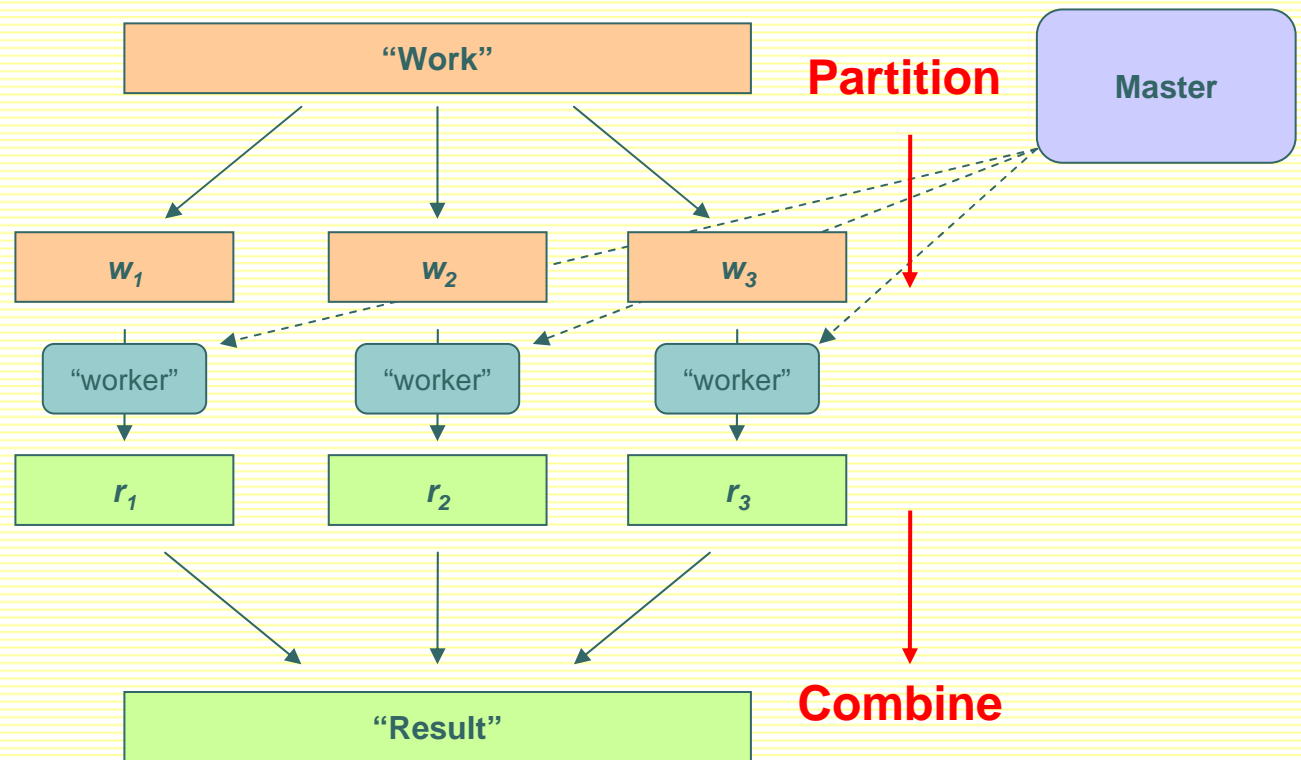
- What does this have to do with HCI?
- Interfaces lies at the end of a long data analysis pipeline:
 - Collection, storage (by machines)
 - Aggregation, filtering, reduction (by machines)
 - Visualization, analysis, manipulation (by humans)

Humans can't interact with what machines can't crunch!



Only Practical Solution (Today)

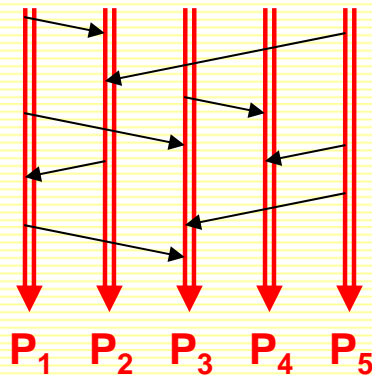
- Divide and conquer
- Throw more machines at it



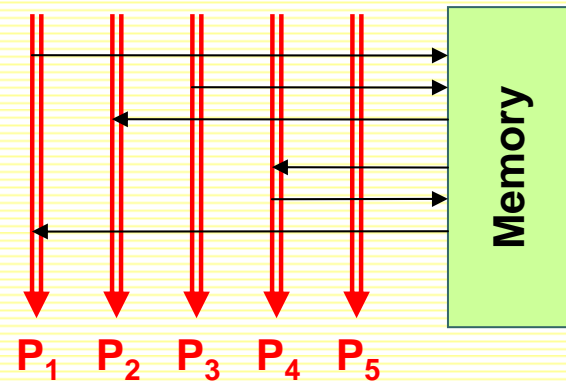
Challenges for Scaling Up

- Issues in parallel and distributed processing
 - Scheduling, data distribution, synchronization, ...
 - Robustness, fault tolerance, ...
- Traditional models for parallel and distributed programming are hard!

Message Passing



Shared Memory



MapReduce in a Nutshell

- General problem structure:
 - Iterate over a large number of records
 - Extract something of interest from each
 - Shuffle and sort intermediate results
 - Aggregate intermediate results
 - Generate final output
- MapReduce provides a functional abstraction:
 - Programmer supplies “Mapper” and “Reducer”
 - Runtime automatically handles everything else!
- MapReduce deployments:
 - Google processes 20 PB a day with propriety implementation in C++
 - Hadoop is an open-source reimplementation in Java



MapReduce Runtime

- Handles scheduling
 - Assigns workers to map and reduce tasks
- Handles data distribution
 - Gets map workers to the data
- Handles synchronization
 - Shuffles data from mappers to reducers
- Handles faults
 - Detects worker failures and restarts
- Everything happens on top of distributed FS
 - GFS = Google File System





“Cloud Computing” Initiative

- Google/IBM’s academic cloud computing initiative (October 2007)
 - Six initial pilot institutions: Washington, Berkeley, CMU, MIT, Stanford, UMD
- IBM provides UMD a Hadoop cluster
 - 20 machines (40 processors)
 - Couple of TB storage
 - Associated infrastructure support
- Maryland does good work with the cluster!
 - Use it to tackle open research problems
 - Use it in the classroom





Cloud Computing Course

- Attempt at integrating teaching and research
 - Pilot course in Spring 2008
 - Basic idea: Ph.D. students leading teams of masters and undergraduate students
 - Goal: tackle “Web-scale” research problems
 - Evaluation: generate publishable results
- What do students get out of it?
 - Everyone learns about MapReduce
 - Undergraduates learn about a particular research area
 - Ph.D. students gain mentoring experience (and help with their work)





Ongoing Projects

- Six teams:
 - Statistical machine translation
 - Reference resolution in email archives
 - Language modeling
 - Biomedical text retrieval
 - Text-image separation in children's books
 - Biological sequence alignment
- Thirteen students
 - 3 undergrads, 3 Masters, 7 Ph.D.
 - From the iSchool, CS, Linguistics, Geography
- Many campus labs involved
 - NLP/IR, HCI, computational biology, etc.



Statistical Machine Translation

Chris Dyer (Ph.D. student, Linguistics)

Aaron Cordova (undergraduate, Computer Science)

Alex Mont (undergraduate, Computer Science)

- Conceptually simple:
(translation from foreign f into English e)

$$\hat{e} = \arg \max_e P(e | f)$$

$$\hat{e} = \arg \max_e P(f | e)P(e)$$

- Difficult in practice!
- Phrase-Based Machine Translation (PBMT) :
 - Break up source sentence into little pieces (phrases)
 - Translate each phrase individually



Phrasal Decomposition

er	geht	ja	nicht	nach	hause
he	is	yes	not	after	house
it	are	is	do not	to	home
, it	goes	, of course	does not	according to	chamber
, he	go		is not	in	at home
it is		not		home	
he will be		is not		under house	
it goes		does not		return home	
he goes		do not		do not	
	is		to		
	are		following		
	is after all		not after		
	does		not to		
	not				
	is not				
	are not				
	is not a				

MT Architecture

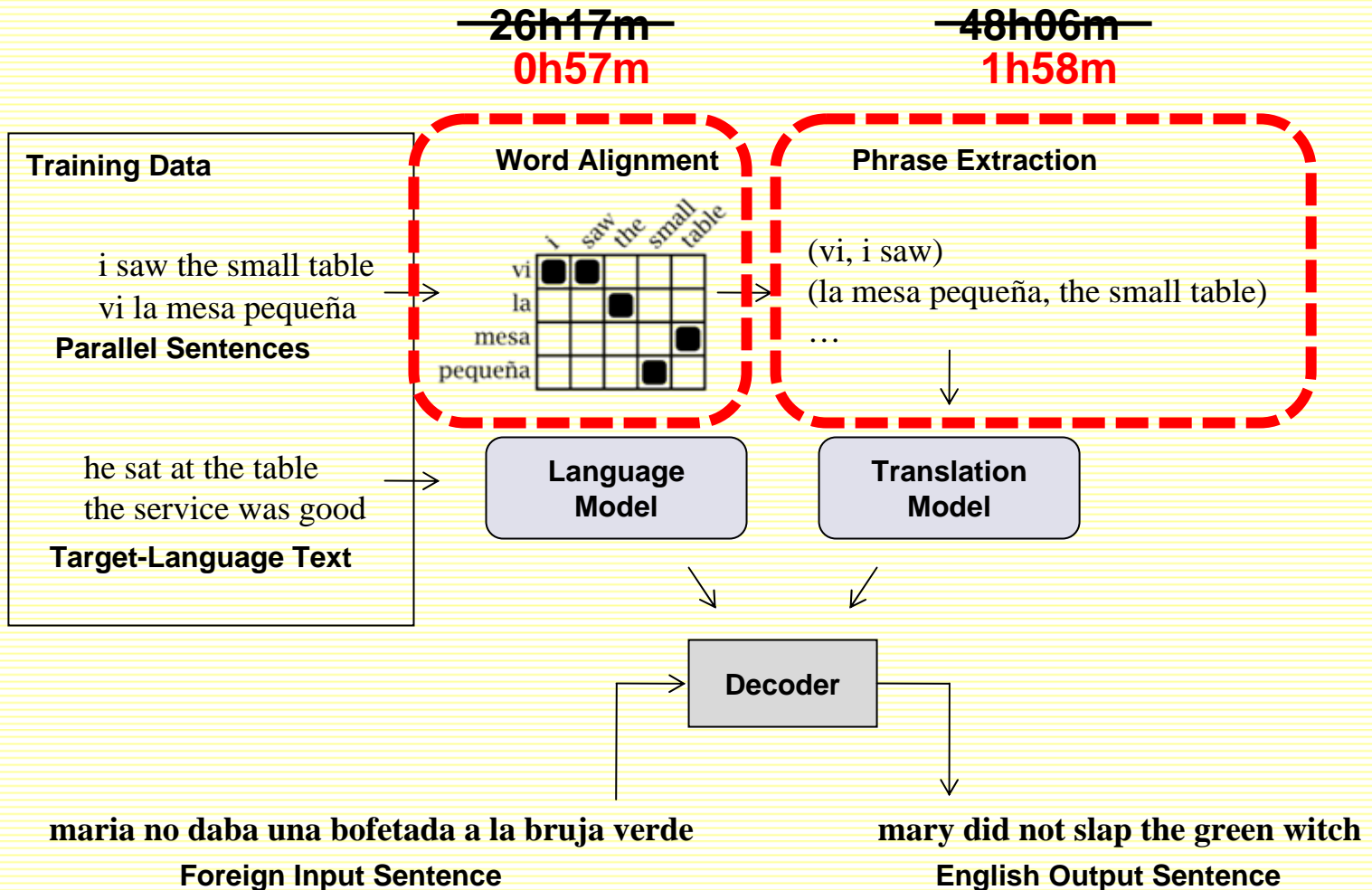


Image Processing

Chang Hu (Ph.D. student, Computer Science),
Punit Mehta (undergraduate, Computer Science)

- Text-image separation in children's books
 - International Children's Digital Library (ICDL):
2412 books, 155,962 pages (and counting)



- Successful implementation in Hadoop
 - Takes advantage of distributed file system



Want to learn more?

- Come to my tutorial tomorrow!
- Topics covered:
 - Overview of parallel and distributed computing
 - Functional programming
 - MapReduce and the Google File System
 - Graph Algorithms with MapReduce
 - Information Retrieval Algorithms with MapReduce



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(iSchool masters)



Alex Mont
(CS ugrad)



Alan Jackoway
(CS ugrad)



Aaron Cordova
(CS ugrad)



Chang Hu
(CS Ph.D.)



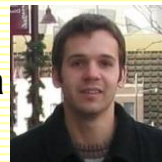
Denis Filimonov
(Linguistics Ph.D.)



Punit Mehta
(iSchool masters)



Hua Wei
(Geography Ph.D.)



George Caragea
(CS Ph.D.)



Mike Schatz
(CS Ph.D.)



Christiam Camacho
(iSchool masters)